On the Use of Fuzzy Inference Systems and Support Vector Machines for Classifying Defects in Metallic Plates

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Abstract. Eddy Current Techniques (ECT) for Non-Destructive Testing and Evaluation (NDT/NDE) of conducting materials is one of the most application-oriented field of research within electromagnetics. In this work, a novel approach is proposed to classify defects in metallic plates in terms of their depth starting from a set of experimental measurements. The problem is solved by means of a system based on wavelets approach extracting information on the specimen under test from the measurements and, then, implementing Fuzzy Inference Systems in order to determine its depth. Shannon Fuzzy Entropy and Subsethood operators have been taken into account to improve the procedure. Finally, a comparison with Support Vector Machines is presented.

1. Introduction to the Problem

NDT in the field of defects identification in metallic elements plays a remarkable role with special regard to those sectors where the integrity of the material is strictly required. The detection of defects in metallic plates together with the relevant shape classification provides the operator useful information on the actual mechanical integrity of the specimen [1]. It should be considered that defects rarely look as well-known geometrical shapes. At the state-of-the-art, non-destructive identification systems allow to locate a defect but without being capable to determine its shape. In addition, different defects give rise to totally similar signals. This paper aims to deal with the classification of defects, both Inner (ID) (the probe lies on the same side of the plate where the defect is located) and Outer (OD) ones (probe and defect are on opposite sides of the plate), in terms of their depth introducing an approach based on Fuzzy Inference Systems (FISs) obtaining banks of IF…THEN fuzzy rules, in virtue of which the system under investigation behaves as a linguistic structure.

A previously proposed pre-processing based on Wavelet Transforms (WTs) is exploited to extract features related to the local trend of the signal. In this way, a device capable to classify defects into two macro-classes have been carried out. In order to refine the procedure, Shannon Fuzzy Entropy (SFE) and Subsethood Operator (SO) which gives a membership measure of a value to an assigned class, have been taken into account. The conventional approaches to classification which assign a specific class for each defect are often inadequate because each defect may embrace more than a single class. Fuzzy set theory, which has been developed to deal with imprecise information, can provide a more appropriate solution to this problem. To compare the obtained results, an approach based on Support Vector Machines (SVMs) obtaining separation hyper-planes among data belonging to different classes is presented. The conventional approaches of classification, which assign a specific class for each defect, are often inadequate because each defect may embrace more than a single class. In particular, exploiting high frequency current probes, it is possible to distinguish, with a very good precision, sub-superficial defects (20%-60% depth); vice versa, by means of low frequency current probes, defects at the bottom of thin metallic plates (40%-100%) can be detected. Therefore, it needs a good calibration of the probes to distinguish a defect in the middle thickness (40%-60%) [2], [3], [4]. Support Vector Machines can provide a more appropriate solution to that problem because they provide a criterion of evaluation to distinguish defects with high, medium or low depth.

The paper is organized as follows: Section 2 reports the characteristics of the experimental database; Section 3 describes the exploited tools and retrieved results and, finally, some conclusions.

2. The Building of Experimental Database

Experimental measurements have been carried out at Non Destructive Testing Lab, DIMET Department, University "Mediterranea" of Reggio Calabria, on a INCONEL 600 specimen from JSAEM (Japan Society of Applied Electromagnetics and Mechanics). It's a plate 140 x 140 x 1.25 mm with four 0.2 x 5 mm rectangular cuts; two are sub-superficial and two are deep cracks (detected into ranges of [20%÷60%] and [40÷100%] of plate thickness respectively). The applied sensor was a FLUXSET®-type probe [2], moved over the specimen by means of a 0.5 mm-step automatic scanning procedure along x and y axes (Fig. 1).

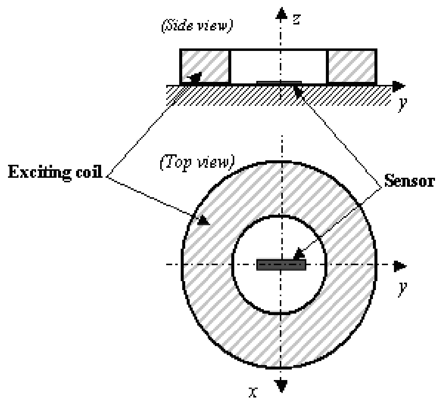

Fig. 1. Schematic draw of the probe.

A 70 x 70 mm central portion of the specimen was investigated this way. A driving signal - triangular shape, 125 kHz frequency, 2Vpp amplitude - was applied to saturate the core material inside the probe. An external sinusoidal exciting field at a frequency of 1 kHz and a current of 107 mArms was generated close to the specimen, thus inducing eddy currents on the surface as well as on subsurface layers. The output pick-up voltage is proportional to the radial component of the induced magnetic field; in the experimental arrangement this component coincides with the component parallel to the longitudinal axis of the sensor itself, that is x axis. 48 full scannings were run and the following 8 outputs were selected (inputs of FIS procedure): the module of the voltage (peak value $|V_{peak}|$, [mV]); the current applied by the signal generator $|i_{gen}|$, [mA]; the frequency of the sinusoidal signal $f_{signal,}$ [kHz]; the five Wavelet Detail Coefficients (WDC) concerning the region where a crack is found. Because the depth measured by the probe does not change during the scan of each defect (just the y position of the probe increases in 0.5 mm steps), the first two classes have been grouped to make a single class, and in the same way with the third and fourth classes. Each input pattern has been linked to a class codification (Table I) representing the crack depth (output of FIS procedure).

Table 1. Codification of FIS output

Class	Codification
ID [20%÷60%], OD [60%÷20%]	1
ID [40%÷100%], OD [100%÷40%]	2

3. The Exploited Tools

FISs allow us to treat and exploit uncertainty [3]. They hold the non-linear universal approximation property, and they are able to handle experimental data as well as a priori knowledge on the unknown solution, which is expressed by inferential linguistic rules in the form IF-THEN (fuzzy conditional statements) whose antecedents and consequents utilise fuzzy sets instead of crisp numbers. The problem can be formulated as the search of a mapping between the set of available measurements and the proposed codify. The inputs of the procedure are interpreted as fuzzy variables. Each fuzzy value carried out by a fuzzy variable is characterised by a Fuzzy Membership Function (FMF) . Each FMF is expressing a membership measure to each of the linguistic properties. FMFs are usually scaled between zero and unity, and they overlap. This overlapping is one of the most useful properties of this approach since it allows an input to be distributed across a number of rules, given rise to an interpolation effect. The typical FMFs are continuous, non-monotonic and piecewise-differentiable functions, such as the commonly used trapezoidal or triangular-shaped functions. To improve the flexibility of our model, Gaussian FMFs have been used. The fuzzy logic approach can be resumed as follows: the use of linguistic variables either in place or in addition to numerical variables; the characterisation of links among variables by using fuzzy conditional statements; the implementation of complex relations by using fuzzy algorithms and calculus. By considering the output variable as a fuzzy variable, one can characterise the relationship between two fuzzy variables (one of input, the other one of output) as a conditional statement of the form IF A THEN B, where A and B are labels of fuzzy sets representing the values of input and output respectively. A FIS is designed according the following procedure: fuzzification of the input-output variables; fuzzy inference through the bank of fuzzy rules; defuzzification of the fuzzy output variables. The design of such a “naive” FIS can turn out to be useful both as a first guess model and when real time systems are concerned. In order to improve the results, a pre-processing based on WTs has been carried out in order to emphasize, if any, characteristics of the signals which are able to furnish a more compact codify of the considered signal.

3.1 WT-based Pre-Processing of Collected Database

WT guarantees the possibility of not specifying in advance the key signal features and the optimal basis functions needed to project the signal in order to highlight the features. A WT is characterized by two functions: the scaling function

$$\phi(x) = \sqrt{2}\sum_{k \in Z} h(k)\phi(2x-k) \tag{1}$$

and its associated wavelet

$$\psi(x) = \sqrt{2}\sum_{k \in Z} g(k)\phi(2x-k) \tag{2}$$

where g(k) is a suitable weighting sequence. The sequence h(*k*) is the so-called refinement filter. The wavelet basis functions are constructed by dyadic dilation (index *j*) and translation (index *k*) of the mother wavelet:

$$\psi_{jk} = 2^{-j/2}\psi(x/2^{-j} - k) \tag{3}$$

The sequences h and g can be selected such that $\{\psi_{jk}\}_{(jk)\in Z^2}$ constitutes an orthonormal basis of L_2, the space of finite energy functions. This orthogonality permits the WDCs $d_j(k) = \langle f, \psi_{jk} \rangle$ and the Wavelet Approximation Coefficients (WACs) $c_j(k) = \langle f, \phi_{jk} \rangle$ of any function f(*x*) to be obtained by inner product with the corresponding basis functions. In practice, the decomposition is carried out just over a finite number of scales *J*. WT with a depth *J* is then given by [6]:

$$f(x) = \sum_{j=1}^{J}\sum_{k\in Z} d_j(k)\psi_{jk} + \sum_{k\in Z} c_J(k)\phi_{Jk} \tag{4}$$

To decompose the considered signal |V|, theoretically choice of Daubechies 2b-level 4 application has been considered, since Daubechies 2 allows to use an adequate compact-support trasform and level 4 allows a good multiresolution analysis, without complications of system and computational load increases. Each signal was divided in four parts (D1, D2, D3, D4): only one of them evidences the defect. Tables 2 and 3 show WDCs (since they are linked to local trend of signal) for jsaem#1 e jsaem#3 (cracks ID, defect on D4), jsaem#6 e jsaem#7 (cracks OD, defect on D1). It can be noticed from Table 2 that WDCs of parts presenting cracks (D4 for jsaem#1 and jsaem#3, D1 for jsaem#6 and jsaem#7) vary at least of one order of magnitude as regards to other parts. At the same time, Table 3 shows that WDCs extracted from signals' portions presenting crack at different depths are also different. Because of these conditions, also the use of WCDs has been decided in order to realize FIS. 40 patterns (DBTrain) have been used to train the FIS, and the remaining 8 patterns (DBTest) have been used for test phase by means of SFE. FIS has been created through Fuzzy Subclustering, on Matlab®, and with non-normalized data, in order to maintain the real context of FIS performance with an RMSE corresponding to real specifications.

Table 2. Analysis of WDCs trend on different parts of the same signal

Signal	Range WDCs in D1	Range WDCs in D2	Range WDCs in D3	Range WDCs in D4
Jsaem#1	$[-3.2*10^{-4}\div8.4*10^{-5}]$	$[-1.1*10^{-4}\div6.3*10^{-5}]$	$[-3.4*10^{-5}\div5.6*10^{-5}]$	$[-7.3*10^{-4}\div1.3*10^{-3}]$
Jsaem#3	$[-1.2*10^{-5}\div5.4*10^{-5}]$	$[-4.1*10^{-5}\div1.9*10^{-5}]$	$[-2.6*10^{-5}\div2.0*10^{-5}]$	$[-2.3*10^{-4}\div2.8*10^{-4}]$
Jsaem#6	$[-2.4*10^{-4}\div3.3*10^{-4}]$	$[-1.6*10^{-5}\div3.0*10^{-5}]$	$[-3.1*10^{-5}\div1.9*10^{-5}]$	$[-1.4*10^{-5}\div3.3*10^{-5}]$
Jsaem#7	$[-9.0*10^{-4}\div1.1*10^{-3}]$	$[-2.6*10^{-5}\div1.2*10^{-5}]$	$[-5.2*10^{-5}\div4.0*10^{-5}]$	$[-1.8*10^{-4}\div3.3*10^{-4}]$

Table 3. Comparative analysis of WDCs on signals' parts showing crack presence

Signal	Crack Depth	Crack segment	WDCs
Jsaem#1	20%÷60% (ID)	D4	$[-7.3*10^{-4}\div1.3*10^{-3}]$
Jsaem#3	40%÷100% (ID)	D4	$[-2.3*10^{-4}\div2.8*10^{-4}]$
Jsaem#6	60%÷20% (OD)	D1	$[-2.4*10^{-4}\div3.3*10^{-4}]$
Jsaem#7	100%÷40% (OD)	D1	$[-9.0*10^{-4}\div1.1*10^{-3}]$

3.2 Fuzzy Hybrid Classification for Middle-Depth Crack Detection

Traditional classification algorithms usually univocally define a defect to a given depth. This depth can be thought as a class (category) of defects. A defect can not belong to more than a class at the same time. These kind of mutually exclusive representations are called “crisp”. Fuzzy sets theory meets this requirement, since it allows a defect to belong to different classes (depths) at the same time, according to the concept of partial membership [3]. Each defect is therefore in principle associable to every class with a partial membership level varying such as $0 \le u_{jk} \le 1$ and

$$\sum_{k=1}^{N} u_{jk} \neq 1 \qquad (5)$$

where u_{jk} is the level of fuzzy membership of *j*th defect to *k*th class (k=1, 2, …, N). Let N classes are given, the shading-type partition produces N informative layers representing membership levels of the defects to the selected classes. Shannon index has been widely applied to evaluate the fuzziness degree of a fuzzy classification. Entropy of a defect, H, its amount of statistic information, is:

$$H = -\sum_{k=1}^{N} u_{jk} \ln u_{jk} \qquad (6)$$

where $\ln u_{jk} = 0$ when $u_{jk} = 0$ [5]. Table 4 shows the classification of 8 patterns of DBTest; 5 pattern of them were wrongly classified (RMSE=62.5%): it is due to location of cracks inside the transition region [40%÷60%].

Table 4. Simulation of classification on DBTest

Signal	Real classification	Simulated classification	SFE values
Jsaem#41	1	1	$SFE_{1,41} = 0.318$ $SFE_{2,41} = 0.351$
Jsaem#42	1	2	$SFE_{1,42} = 0.322$ $SFE_{2,42} = 0.102$
Jsaem#43	2	2	$SFE_{1,43} = 0.052$ $SFE_{2,43} = 0.032$
Jsaem#44	1	2	$SFE_{1,44} = 0.094$ $SFE_{2,44} = 0.008$
Jsaem#45	2	1	$SFE_{1,45} = 0.004$ $SFE_{2,45} = 0.181$
Jsaem#46	2	1	$SFE_{1,46} = 0.003$ $SFE_{2,46} = 0.116$
Jsaem#47	1	1	$SFE_{1,47} = 0.009$ $SFE_{2,47} = 0.200$
Jsaem#48	2	1	$SFE_{1,48} = 0.007$ $SFE_{2,48} = 0.195$

SO [2] of each i^{th} pattern of DBTest for each k^{th} class has been used to identify if misclassified cracks are located into the [40%÷60%] of plate thickness. The nearer to 1 $S_{k,I}$ is, the more the i^{th} pattern belongs to the k^{th} class; the nearer to 0 $S_{k,i}$ is, the less the i^{th} pattern belongs to the k^{th} class; the nearer to 0.5 $S_{k,i}$ is for each class, the more its matching class is indefinable. Table 5 shows SO values for misclassified cracks; it proves how errors of SFE-based classifier was due to defects located into the deepness transition region [40%÷60%].

Table 5. Subsethood values

Signal	Jsaem #41	Jsaem #42	Jsaem #43	Jsaem #44	Jsaem #45	Jsaem #46	Jsaem #47	Jsaem #48
$\mathbf{S_{1,k}}$	0.636	0.568	0.392	0.554	0.539	0.590	0.783	0.569
$\mathbf{S_{2,k}}$	0.408	0.521	0.816	0.481	0.524	0.550	0.348	0.536
SFE class.	1	2	2	2	1	1	1	1
Trans. region	No	Yes	No	Yes	Yes	Yes	No	Yes

3.3 Middle-Depth Crack Detection: SVM-based Validation

A support vector classifier attempts to locate a hyperplane that maximises the distance from the members of each class to the same hyperplane. BSVMs have been introduced within the framework of the Statistical Learning Theory which describes the principle of Structural Risk Minimization (SRM). Considering a support vector classifier [7], the error probability is upper bounded by a quantity depending by both the error rate achieved on the training set and a measure of the "richness" of the set of decision functions it can implement (named "capacity", or Vapnik Chervonenkis dimension). The more the set of decision functions is rich, the higher is the classifier's capacity, and the upper bound on the error probability can increase for increasing values of the capacity. This principle aims at reaching the minimum of the upper bound on the error probability of a classifier, by achieving a trade-off between the performance on the training set and the capacity [7], [8].

In this section, a validation of proposed heuristic approach is described by a comparison with an SVM-based approach. In particular, a polynomial SVM have been trained by using DBTest. Table 6 shows the classification of 8 patterns of DBTest; 5 pattern of them were wrongly classified (RMSE=62.5%).

Table 6. Simulation of classification on DBTest

Signal	Real classification	Simulated classification	Signal	Real classification	Simulated classification
jsaem#41	1	1	jsaem#45	2	1
jsaem#42	1	2	jsaem#46	2	1
jsaem#43	2	2	jsaem#47	1	1
jsaem#44	1	2	jsaem#48	2	1

Retrieved results confirm how same defects are misclassified by SFE-SO hybrid method as well as by SVM-based approach. This could be a proof that misclassified cracks are located in the middle depth [40%÷60%] of investigated plate. Therefore, in order to confirm this hypothesis, the Confusion Matrix (so-called CM') [7], computed by means of misclassified cracks, has been calculated. Generally speaking, the element CM_{ij} of a Confusion Matrix is the probability that a single pattern belonging to the i^{th} class could be classified as belonging to the j^{th} class (sum of elements of each rows is therefore equal to 1). Thus, if elements of CM' are next to 0.5, misclassified defects have the same probability to belong to the two class of defects, i.e. they belong to the middle-depth region of inspected plate. Calculated CM' appears as follows:

$$CM' = \begin{bmatrix} 0.526 & 0.474 \\ 0.512 & 0.488 \end{bmatrix} \quad (7)$$

Information carried out by CM' involves the whole set of misclassified cracks; since elements of CM' are very close to 0.5, information can be itemized for each element of the same set, i.e. it is possible to affirm that each misclassified cracks belongs to the transition zone ([40%÷60%]).

4. Conclusions

In this paper a novel approach to classify defects in metallic plates in terms of their depth starting from a set of experimental measurements is proposed. Firstly, FISs, SFE and SO have been taken into account to solve the problem of "multi-membership" of defects to several categories. A pre-processing phase has been carried out by means of WTs, with the extraction of features related to local trends of the signals. In classification phase, an hybrid SFE-SO system has been used in order to determine the defect's depth and quickly classify results with low-computational complexity algorithms. A classification has been carried out on three depth ranges ([20%÷40%], [40%÷60%] e [60%÷100%]), therefore extending the scientific applications of the Fluxset device.

Subsequently, SVMs and CMs have been taken into account to validate an heuristic approach in middle-depth crack classification. By SVM it is possible to design a separation hyperplane among eddy current parameters to correctly classify depth of defects. The advantages of this approach can be resumed as follows:

- it is possible to simplify the problem by a mapping from the physical space to the feature space;
- it is possible to explain the system in terms of point in the features space with a direct physical interpretation;
- the SVM model is parsimonious with respect to other techniques also in terms of computational complexity of real time operating phase. At the very last, this approach is motivated by the possibility of having a rapid model of the classification block; by using learning techniques, the model could be well refined to become competitive with different traditional approaches;
- the results obtained by using any rapid mapping prototype can be compared to those obtained by an off-line most accurate as well as time-consuming analysis for validation;
- the proposed approach can be considered as an on-line system.

In classification phase, an hybrid system based on polynomial SVM and CM (with its improved modification CM') has been used in order to determine the defect's depth and quickly classify the results with low-computational complexity algorithms. SVM-based approach confirmed results retrieved by Fuzzy hybrid approach: Table 7 shows the depth of each crack for DBTest data as retrieved by proposed Fuzzy and SVM-based methods.

Table 7. Crack depths of DBTest

Signal	**Depth**	**Signal**	**Depth**
Jsaem#41	[20%÷40%]	Jsaem#42	[40%÷60%]
Jsaem#43	[60%÷100%]	Jsaem#44	[40%÷60%]
Jsaem#45	[40%÷60%]	Jsaem#46	[40%÷60%]
Jsaem#47	[20%÷40%]	Jsaem#48	[40%÷60%]

With respect to Fuzzy approach, which uses a classification procedure composed by three steps (FIS, SFE and SO) the approach exploiting SVM is characterized by a simpler classification structure. In particular, just two steps (SVM-based classifier & CM calculation) are needed. On the other hand, SVM appears as a "black-box" solution, not allowing self-extracted definitions of user-friendly empiric rules.

In conclusion, our different heuristic approaches allows to classify cracks in smaller and separated intervals of deepness, with high performances and reduced computational load, this way avoiding the presence of indecision regions, useful in real-time applications. It is worth mentioning that the interesting results achieved are susceptible of improvement by implementing the network structure some a priori rules possibly available.

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